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The effect of noise content and level on cognitive performance measured by electroencephalography (EEG)

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ABSTRACT

Task-irrelevant noises pose deleterious effects on task performance, health, and work safety, especially in the construction field. However, the quantitative effects of noise on the cognitive performance in construction remain relatively unexplored. The paper aims to examine the effects of various noise conditions on task performance and cognitive performance via a portable electroencephalography device. A total of 27 subjects participated the experiment to identify hazards under different noise exposure conditions (contents and levels). The behavioral performance (accuracy and reaction time) and electroencephalography were collected and analyzed. The findings indicated a negative relationship between the performance of the participants and the exposure to noise. The intrinsic cognitive states including attention, stress and mental workload have been affected in varying degrees. Evaluating the impact of noise on cognitive functions helps explain the mental effects of the impaired performance. Neurocognitive monitoring with electroencephalography sets the basis for predicting task performance under different noise conditions.

1. Introduction

Occupational task-irrelevant noises represent a chronic risk to work performance, safety, and personal health, especially in the construction industry. Construction activities can generate potentially hazardous noise across different stages [1]. It has been reported that prolonged exposure to noise strongly correlated with extensive adverse effects, which include work disturbance, speech interference, hearing loss, impaired task performance, increased annoyance level, degraded hazards perception ability, and even increased accident risks [2–4]. Some studies argue that noise negatively impacts safety due to the increase in work errors and interference in safety communication and alarms [4–6]. Additionally, noise-induced cognitive effects like loss of attention and increased stress can indirectly contribute to accidents [7].

To gain a more in-depth insight into the implications of noise at workplaces, it is crucial to explore the relationship between noise and behavior and develop noise mitigation strategies [8]. Previous studies have examined the factors and controls of adverse noise impacts, taking into account the acoustic characteristics, personal, task-based, and situational factors [9]. Among all factors, the level of noise has drawn the most attention given that construction noise is generally at a high level (e.g., noise exposure for equipment operators), exceeding the regulation limits [10,11]. It has been found that noise level varies primarily depending on the type of construction activities and machinery in use [1]. Previous efforts mainly emphasized the impacts of noise levels on occupational health (such as hearing problems) and task performance, paying less attention to the intrinsic effect of noise on cognitive functions. Yet, the cognitive functional changes due to the exposure to noise are fundamental for understanding the decreased performance and unsafe behaviors [12]. There is a pressing need to unveil how noise affects the cognitive functions of construction workers.

Noise on the construction site is difficult to control because of the variety of noise sources and the constant changes to construction tasks. Several studies highlighted the importance of noise content in addition

Abbreviations: EEG, Electroencephalography; NIHL, Noise-induced hearing loss; NIT, Noise-induced tinnitus; HPD, Hearing protection device; RT, Reaction time; TLX, Task load index; ISE, Irrelevant speech effect; HRV, Heart rate variability; CG, Control group; MUG, Music group; DG, Dialogue group; LMG, Low mechanical noise group; MMG, Medium mechanical noise group; HMG, High mechanical noise group; EMG, Electromyography; ICA, Independent component analysis; ASI, Asymmetry index; RA, Response accuracy; SD, Standard deviation; DWT, Discrete wavelet transform; MWL, Mental workload.

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to the level of noise [13,14]. Noise has been defined as the undesired sound that intervenes with work. It is mainly driven by the construction equipment but could be from other sources in construction workspaces. Because mechanical noise is the most prominent one, little research effort has focused on other possible noise sources such as mobile phone ringtones, playing music, and colleagues' conversations. Although other noise sources may not be persistent compared with the mechanical noise, occasional sounds cannot be ignored, and intermittent sounds even have more harmful disturbance than continuous noise [15].

To fill the gap, this study examines the neurophysiologic reactions to varying noise levels and contents, in order to promote the understanding of the cognitive basis of noise impacts. The remainder of this paper introduces the theoretical basis of this research, and findings from a human-subject experiment.

2. Literature review

The section reviews work examining the adverse noise effects and important factors. Afterward, previous studies concerning the effect of noise on cognitive performance were discussed. Lastly, the measures of cognitive state and selected EEG indicators were listed.

2.1. Noise effects and factors in construction workplace

The noise-induced effects are most commonly classified into auditory and non-auditory categories [16]. Auditory effects primarily refer to hearing damage like noise-induced hearing loss (NIHL), noise-induced tinnitus (NIT), and even deafness that can be permanent if noise frequently exceeds the threshold limit like 85 dBA [17]. When auditory damages are likely to occur, hearing protection devices (HPDs) are adopted to reduce hearing loss [18]. However, the role of HPDs is mixed as the exposure to a controlled certain extent noise may impede the ability to retrieve and process surrounding information. In addition to hearing loss, people exposed to noise hazards may suffer other noise-related health problems like cardiovascular diseases and mental disorders [19,20]. Non-auditory effects encompass behavioral performance, workplace safety, information processing, annoyance, speech interference, cognitive impairment, concentration, stress, emotions, etc. As for the construction sector, the majority of researchers focused on hearing loss and its protection [9,18]. Nonetheless, safety risk derived from noise exposure cannot be underestimated, especially for those involved in safety-critical works or tasks demanding a higher cognitive ability. Noise, as one of the environmental contaminates, is a long-term and invisible risk leading to unsafe behaviors and accidents [21,22].

With respect to the effect of noise on behavioral performance, there are conflicting findings on response accuracy and speed in the relevant literature, as shown in Fig. 1 and Table 1. On the one hand, some studies found that noises indeed facilitate performance [23]. A possible explanation is that noises can add stimulus and increase arousal to relatively monotonous tasks, thus improve vigilance and task engagement. On the other hand, another study [24] proved that noises would cause accuracy degradation yet help response speed mainly due to the accuracy-speed trade-off. Increased reaction time (RT) and errors caused by noise exposure are also found by an empirical study [25]. Evidence shows that noises would slow down the response time for information processing [26], crucial for evacuation speed in emergency circumstances. Nevertheless, some advocated that noises merely impose a weak effect on accuracy and speed [8]. Similar to previous studies, accuracy and reaction time of risk identification act as critical metrics of safety performance, which were also adopted to assess the effect of noise exposure in this paper.

Noise effects differ in various aspects, including acoustic characteristics as well as personal, task-based, and situational aspects. Noise sensitivity driven by personal factors remains the most explored topic as

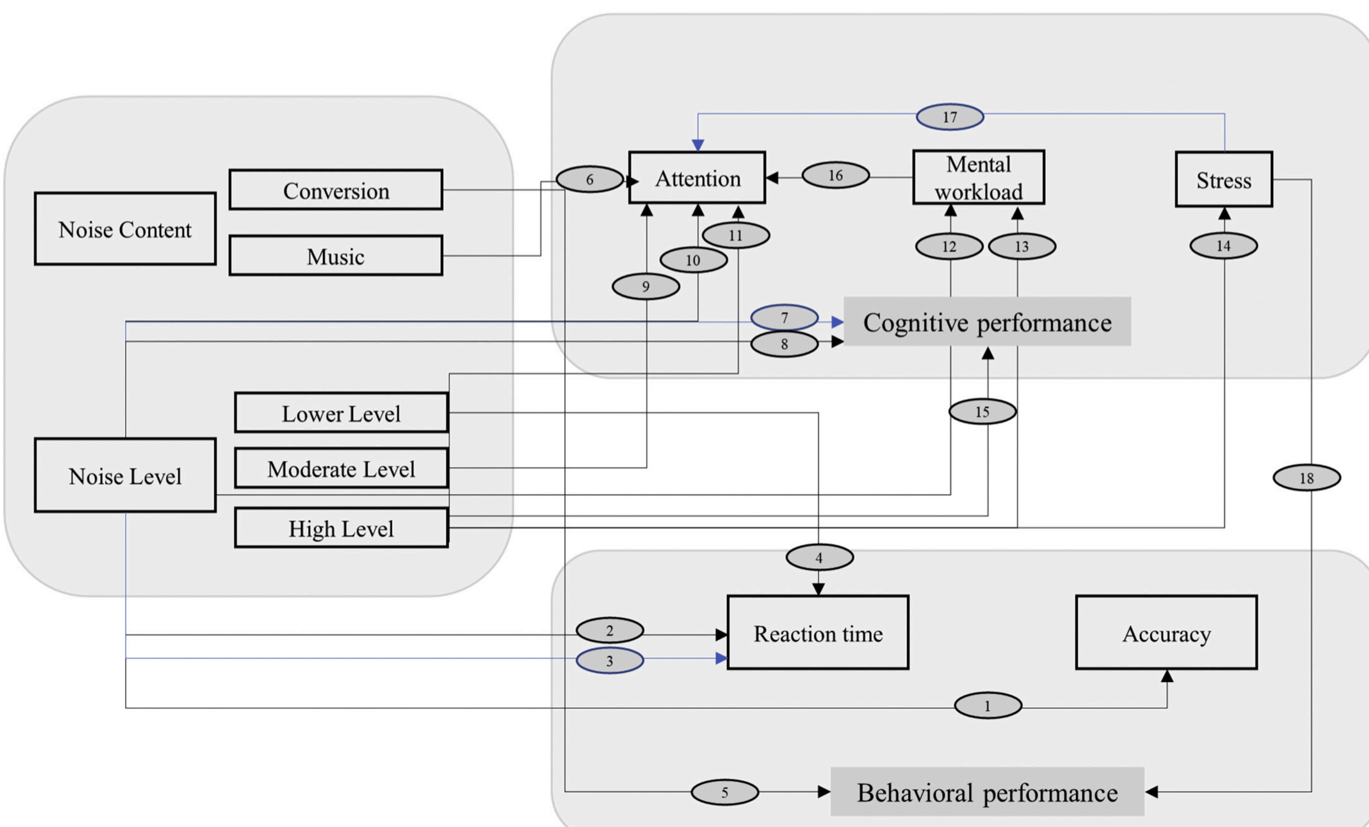

Fig. 1. The effect of noise exposure on behavioral and cognitive performance and interrelation (the blue and black line represent the positive and negative effect, respectively). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Corresponding relationship introduction to Fig. 1.

Effect	Serial number	Relationship	Description	Reference
The effect of noise on behavioral performance	1	Negative	Noise exposure increased errors	[25]
	2	Negative	Noise exposure causes a longer reaction time	[24,25]
	3	Positive	Noise reduced reaction time	[24]
	4	Negative	RT is higher with lower noise levels	[13]
	5	Negative	Speech noise effect more significant than non-speech noise	[24]
	6	Negative	Pop songs with lyrics (music) distract more attention than noise under high volume	[10,14]
The effect of noise on cognitive performance	7	Positive	Noise improved cognitive function	[23]
	8	Negative	Noise has reduced cognitive function	[12,27]
	9	Negative	Medium levels of occupational noise affect attention	[13]
	10	Negative	Noise exposure reduced attention	[28]
	11	Negative	High levels of noise significantly reduced attention levels	
	12	Negative	Noise exposure increased mental workload	[29]
	13	Negative	Higher noise caused a higher mental workload	[13]
	14	Negative	Noise exposure higher than 85 dB causes stress	
	15	Negative	The higher level at 95 dB reduced cognitive performance	[30]
	16	Negative	The increase in mental workload distract attention	[13]
	17	Positive	Stress increased attention	[31]
The relationship between cognitive and behavioral performance	18	Negative	High-stress situations, performance is reduced	[32]

it has been proven that the noise sensitivity's effect on noise annoyance and job stress is more potent than the effects of other factors like gender and age [1,33,34]. Noise' auditory characteristics include its level, tonality, content, frequency, impulsivity, spectrum, stability, variability (fluctuation vs. intermittent), distribution, and exposure duration [2,8,11]. A large number of experimental and survey studies have been carried out to assess the effect of noise level and exposure duration by field measures [35]. Furthermore, a direct negative relationship between noise level and performance has been validated by several studies [26,36]. The noise level is the most influential parameter but usually centered on a higher level of noise, not a wide range. A previous study [13] pointed out that a moderate level of noise has been seldomly discussed. For instance, construction workers in offices may often be exposed to medium levels of noise, while frontline equipment operators are usually exposed to high noise levels. Herein, this study's range of noise level was set into three levels: low, medium, and high.

Noises are generated by multiple sources, of which machine-produced and activity-made noises have been considered the default sources in construction fields. However, there has been a tendency to overlook the implications of the noises from human-made sources and mobile devices. For example, studies indicate that intermittent speech-based noise like the conversation has a more tremendous effect than continuous non-speech noise [24]. Hence, noise content mentioned above was also selected as one of the variables since the shift in noise content may split workers' attention according to the changing-state effect, which changes the element of background sound thus is more harmful than the changeless sound [37]. It shall be noted that labors who have more work experience may have adapted to mechanical noise; hence other noise sources of noises may be more disruptive for ongoing task performance. The same noise in different task environments also changes noise effects, such as the working memory task, visual or auditory perceptual task, information processing task, physical activities, communication tasks, etc. As a result, it is necessary to specify the task context when assessing the impact of noises. This research focuses on safety-critical tasks, of which hazardous holes and openings identification is a prevalent visual task in daily work. With that said, this research examined how noises affect safety performance in a hazard identification task.

2.2. *The cognitive effect of noise*

The effect of noise emission on cognitive performance is significant [21]. Excessive exposure to noises can be fatal for workers in safety-related positions or vital occupational roles that demand a proper and sustainable cognitive performance. Several studies have linked increased noise levels to impaired cognitive performance [12,15,30]. Furthermore, the noise effects can pertain to both behavioral and cognitive related performance. Cognitive performance refers to the performance during a series of cognitive processes, such as perception, memory, retrieval, judgment, and decision making [38]. Cognitive performance is associated with the dynamic cognitive states. Most articles have concentrated on the direct effects of noise on external performance, error rates, and so on [8,36]. However, the existing evidence is inadequate regarding the noise effects on cognitive performance, which can be assessed by the cognitive state, such as stress level, attention level, cognitive load, annoyance, etc.

Some studies have suggested that two of the most significant effects of noise on cognitive performance are distracting attention and short-term memory [39–41]. It is known that attention plays a significant role in cognitive functions such as perceptual, information processing, and strategy selection. Noise can divert attentional focus on the task at hand, but each employee's attention resource is limited. One of the reasons accounting for affected information processing capacity is limited attention resources, while variable task demands and environmental distractors, including noise, compete for the same attention resources concurrently [42,43]. Whether specific characteristics of noise deprive more attention resources is our concern. In addition to the attentional-resource-based perspective, over-arousal invoked by noise would elicit attentional narrowing derived from the arousal theory, which decreases the breadth of attention [44]. The consequence of attentional narrowing is filtering out primary task-related information, leading to a decline in performance. However, when the noise-induced mild arousal does not exceed the threshold, attentional change is not pronounced even is beneficial to cognitive control [24]. Assessing attention enables us to characterize the effect of noise on attentional level change during task implementation. Due to the task in this experiment is about hazard identification with little memory demand, short memory was not discussed in this paper.

The study of noise effect on mental workload and stress has received relatively less concern compared to attention. The concept of mental workload is broader than that of working memory load: the former is overall perceived load while the latter refers, in particular, to load in encoding and recalling information during the process of performing a task. Understanding mental workload is of great significance to human factors research into degraded performance [45,46]. For instance, the speech condition in open offices causes a significant decline in performance and the increase in mental workload measured by the NASA Task Load Index (NASA-TLX) compared to one in a quiet condition, which supports the detriment of irrelevant speech effect (ISE) [29]. A prior study argues that noise increases mental workload because of the decreased available cognitive resources for tasks [47].

Similarly, the distinct degrees of stress disturbs the cognition functions through the autonomic nervous system and emotional systems [48]. Some studies have reported that a higher level of noise would elicit stress, which proves that noise condition has a direct connection with increased job stress [49,50]. However, an early study and consistent conclusion indicated no difference in perceived stress between quiet and noisy conditions was observed despite enhanced workers' urinary epinephrine levels [51,52]. Given that mental workload and stress belong to essential moderators in cognitive functions and are significantly related to the ability to perceive risk, the authors adopted attention, stress levels, and mental workload as evaluation metrics.

Therefore, there is a research gap to quantify the impact of noise on the cognitive states (involving attention, stress, and mental workload), and explore the underlying mental reason of behavior shaping.

2.3. Cognitive state metrics by EEG

The measures of cognitive state can serve as the tool to monitor performance as well as to provide neurofeedback mainly applied in safety-critical scenarios. Countermeasures aimed at noise pollution can be divided into sources, receiver, environment [2]. Two main lines of research concern how to avoid noise sources and block the receiving. However, noise exposure in some scenarios is inevitable and difficult to eliminate. The neurophysiologic parameters can help to explore the dynamic mental process in noisy environments. Approaches of cognitive state assessment consist of subjective survey and objective techniques. Subjective questionnaires, a type of retrospective feedback, lack reliability and are susceptible to perception at a particular moment. Previous studies have demonstrated that noise can be switched from being acceptable to annoying across periods [2]. Noise may have little effect at first but becomes distressing later. Consequently, the detection of cognitive state can be objectively achieved by biological devices, addressing the limitations that the existing literature primarily examined the subjective perception of cognitive noise effect. With the help of physiological measurement, objective measures include EEG, heart rate variability (HRV), eye movements and blinks, skin conductance and so on. One of the promising approaches is EEG owing to its portability, noninvasive advantages, and high temporal resolution. EEG is a valuable tool to evaluate cognitive performance by brain signals and activity patterns.

A distinct cognitive state corresponds to different indicators, some of which are controversial due to different experimental tasks. After screening related literature, three indicators were selected and summarized in Table 2. According to the frequency, EEG waves are commonly divided into five basic bands: delta (1–4 Hz), theta (5–7 Hz), alpha (8–14 Hz), beta (15–30 Hz), and gamma (>30 Hz). Theta/beta ratio recorded from frontal regions is considered a valuable biomarker of attentional control, which has a negative relationship with attentional control [53]. An EEG asymmetry index of alpha activity is a frequent feature to assess stress levels during emotional arousal, which appears to decrease during stressful conditions across most stress-related studies [54]. Besides, the energy of the approximate coefficients of wavelet parameters would decrease with increased workload level [55].

According to the overview above, three hypotheses were proposed:

Table 2
Cognitive performance measurement metrics.

Cognitive State	Index	Channels	Correlation	Reference
Attention	Theta/beta power at prefrontal locations	AF3, AF4, F3, F4	–	[53,56]
Stress	Asymmetry index (ASI) of alpha power at the lateral frontal cortex	F7, F8	–	[54,57]
Mental workload (MWL)	The energy of the approximation coefficients at frontal lobe	AF3,AF4, F3,F4,F7, F8,FC5,FC6	–	[55]

Note: Channel refers to the electrodes located at the EEG device according to the international 10–20 system. "-" represent significant negative correlations.

(1) Noise content will affect risk perception, behavioral performance (response time and accuracy), and cognitive performance (attention, stress, mental workload level).
(2) Noise level will affect risk perception, behavioral performance (response time and accuracy), and cognitive performance (attention, stress, mental workload level).
(3) Behavioral and cognitive performance are interrelated.

3. Experiment design by noise stimuli

The main objective of this experiment was to quantify the effects of task-unrelated sounds on safety behavior and cognitive performance in the construction field. The safety-related task adopted is common hazardous hole identification. This experiment was carried out in a laboratory environment. The noise stimuli and experiment procedures are introduced as follows.

3.1. Participants and apparatus

The participants were 23 male and 4 female undergraduate students, who aged from 18 to 25 years old. The eligibility principles for the recruitment of participants included good health, normal vision and hearing, and noise tolerance. The respondents voluntarily signed up for this experiment and obtained compensations. Besides, after briefing the participants on the study's purpose and nature, informed written consent was obtained from each participant. Emotiv-EPOC with 14 electrodes via saline wet were used to collect the continuous brain waves. The electrodes are mounted at the frontal (AF3, AF4, F3, F4, F7, F8, FC5, FC6), temporal (T7 and T8), parietal (P7 and P8), and occipital (O1 and O2) regions, along with two reference electrodes (CMS/DRL located at P3 and P4), as illustrated in Fig. 2. The placement is in accordance with the international 10–20 system of electrode placement. The apparatus complies with safety standards, including radiofrequency emissions and electrical safety, and fully certified as C*E*-marked. Therefore, this experiment was approved by the Ethical Research Committee at the City University of Hong Kong. The version of the experiment's task implementation is E-Prime 3.0, a professional psychological experimental presentation software, which is also responsible for recording behavioral data including precise reaction time and keyboard response [58].

3.2. Trial and procedure design

The experiment used a dual-task design and sustained attention to response paradigms. This experiment presented images on the computer screen. The contents of the collected images are sixteen common types of hazardous holes and openings in the construction site, such as the floor and wall openings, as listed in Fig. 3.

The authors explained the tasks and procedures (shown in Fig. 4) to the subjects before the formal experiment, and training sessions were carried out until they are familiar with the tests. The experiment began

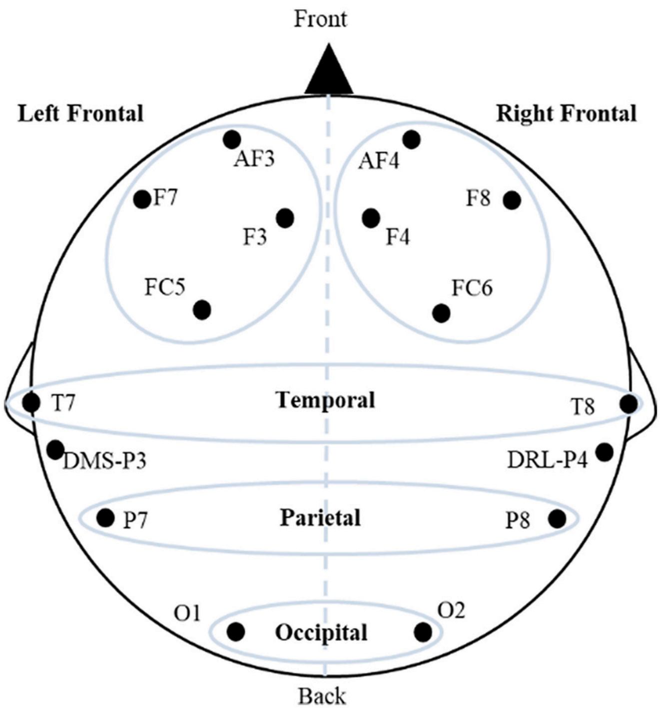

Fig. 2. Electrodes and regions layout of Emotiv-EPOC.

with detailed instructions, and the subjects can begin on their own when they were ready while recording the brain waves synchronously by EmotivPRO software.

Each trial presented six random images simultaneously for six seconds. The participants were asked to determine whether there is any picture of the hole containing safety hazards and then press the button numbers 1 to 6 on the keyboard as feedback. If not, press number 7, as demonstrated in Fig. 4. Each set of 30 stimuli had a 70% chance of appearing a potentially dangerous hole and a 30% chance of presenting none at all, aiming to reduce random guesses' probability by the setting. The experiment consists of six groups, as presented in Fig. 4. The content or level of sounds presented are distinct for each group: the control group (CG), the music group (MUG), the dialogue group (DG), the low mechanical noise group (LMG), the medium mechanical noise group (MMG), and the high mechanical noise group (HMG). A probe at the end of each group, inquiring the subjective attentional level assessed by question Q1 [59,60] listed in Table 3. In addition, performance markers including EEG indicators have been combined to evaluate varying degrees of task attention engagement. After completing all the group testing, the subjects were asked to answer the remaining two questions (Q2 and Q3) in Table 3. Six sessions were done at once for each participant. To avoid the order effect and practice effect, the order of six sessions for each participant is completely random. This also reduced the effect caused by the change of tolerance to noise between sessions. The test for each participant last for about 30 min. During the whole process, the experimenters were keeping an eye on data recording quality to make sure good contact between wet sensors and scalp.

3.3. Noise stimuli presentation

Three frequent types of sounds were implemented, including mechanical noise, music, and conversational dialogue. The noise was collected from the Google search engine. The dialogue was crosstalk to simulate an interesting conversation between two employees. The music presented was pop music with lyrics, and the mechanical noise consisted of various mechanical operations from construction equipment (e.g., compactor, hammer, and driller). The noise intervention was achieved by in-ear headphones. The environment in which noise was displayed is an acoustically insulated room (H = 3 m, L = 9 m, and W = 5 m). The estimated level at the maximum volume of earphones is 113.1dBA [61], and the author calculated the presented level of noise according to the ratio of the volume cell. The noise level of CG, MUG, DG was the same with the MMG (70dBA), while the level at LMG and HMG (60dBA vs. 80dBA).

4. Data analysis methods

Behavioral metrics by E-prime and brain activities by EEG were obtained. This section introduces methods used to analyze metrics in both behavior and cognitive state, and relationship analysis was proposed to explore the interrelation.

4.1. Behavioral performance analysis

The key metrics are reaction time and the accuracy of hazard identification. The statistical analyses were performed using SPSS (version 26.0). The percentage of the correct answers was calculated, and the right and wrong response trials were discriminated against separately. The average reaction time of all trials, right trials, and wrong trials obtain statistical results, respectively. Given that the data of reaction time rejects normality and the two samples' size is not consistent, the Mann-Whitney U test was conducted to examine the differences in reaction time according to the answers. After testing the homogeneity of the variance by Levene's test and the normal distribution of the data by the Shapiro-Wilk test, the data of behavior performance data and rating scores reject normality and the population variances are significantly different. Therefore, the Kruskal-Wallis ANOVA test from non-parametric methods was used to validate the difference of noise effect content and level on response accuracy, reaction time, and rating scores among multiple groups.

4.2. EEG indicators calculation

The analysis of brain waves by EEG was comprised of two stages: data preprocessing and indicators calculation. The preprocessing step is essential for the removal of artifacts. Throughout the whole process of EEG wearing, the data acquired is vulnerable to various artifacts, which primarily include intrinsic (individuals' eye blink, eye drift, muscle) and extrinsic (the possibility of electrode movement, sweat interference, power line interference, surrounding noise interference) artifacts. The contamination of audible noise on the data was negligible due to the noise stimuli was achieved by in-ear ways. Hence, for extrinsic artifacts, the raw data was firstly filtered by band-pass (1–64 Hz) and notch (50 Hz) filters to remove power line rejection. The step was followed by interpolating bad channels (according to the recording quality <90% assessed by recording software EmotivPro) and rejecting poor periods, which were caused by individual movement and poor contact between scalp and electrodes by visual inspection. For intrinsic artifacts, independent component analysis (ICA) was performed to calculate components by EEGLAB toolbox [62]. Related contaminant components about eye movement and blink and muscle artifacts were rejected. According to the total duration of 30 trials in a group, the EEG signals of a subject in each group were segmented into 30 epochs using a time window of $T = 6$ seconds.

The filtered data was secondly analyzed by wavelet decomposition into sublevels using MATLAB. Wavelet decomposition, one of the discrete wavelet transform (DWT) methods, is time-frequency analysis methods applied to non-stationary signals like EEG. Convolving a signal x(n) with successive high pass and low pass filters, followed by down-sampling, results in coarse-scale approximation coefficients (cA_1) and detail coefficients (cD_1) of first level [63], as the following formulas show:

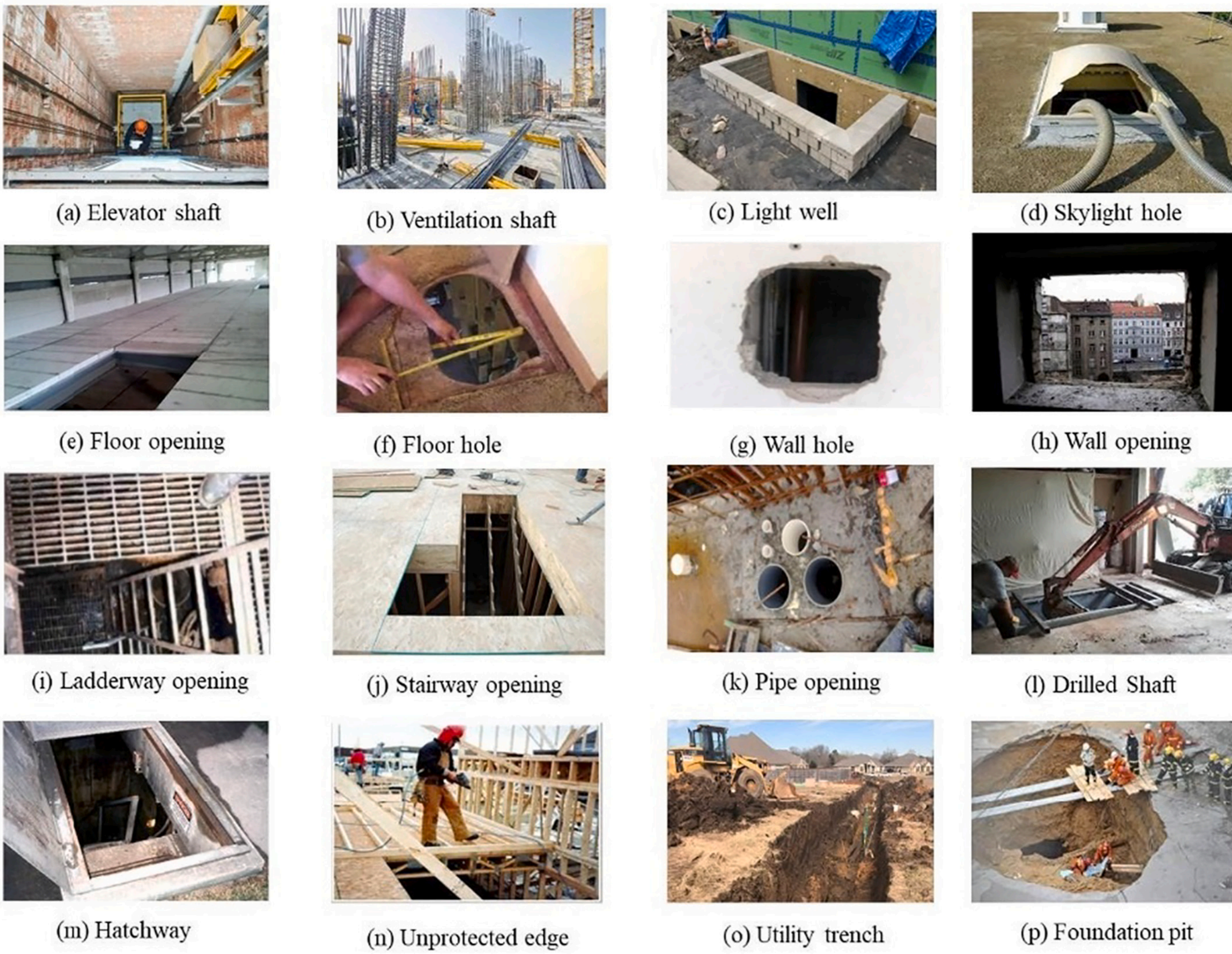

Fig. 3. Hazardous hole categories presented in the experiment.

$$\varphi_{j,k}(n) = 2^{j/2}h\left(2^{j}n - k\right) \tag{1}$$

$$\psi_{j,k}(n) = 2^{j/2}g\left(2^{j}n - k\right) \tag{2}$$

where $\varphi_{j,\,k}(n)$ is the dilation function of the low pass filter $h(n)$, $\psi_{j,\,k}(n)$ is the wavelet function following the high pass filter $g(n)$. And$n \in \{0,1,2,\ldots,N-1\}$, $j \in \{0,1,2,\ldots,J-1\}$, $k \in \{0,1,2,\ldots,2^{j}-1\}$, $J = \log_2 N$, N is the length of the signal x(n). In this paper, $N = Tfs = 768$ time points (sampling rate is 128 Hz).

The coefficients including approximation and detail coefficients were calculated by dot products between the original signal and the wavelet basis functions as follows:

$$cA_i = \frac{1}{\sqrt{N}}\sum x(n) \times \varphi_{j,k}(n) \tag{3}$$

$$cD_i = \frac{1}{\sqrt{N}}\sum x(n) \times \psi_{j,k}(n) \tag{4}$$

where cA_i represents the approximation coefficient at the i level. The cA_1 was further disintegrated and the process repeated until the number of levels that we specify is reached, as shown in Fig. 5. The order 4 Daubechies (db4) was adopted as wavelet scaling function and the signal was decomposed to four wavelet levels, which correspond approximately to its frequency band. We obtained detail (cD_1, cD_2, cD_3, cD_4) and approximate (cA_4) coefficients, respectively [64].

Then, the total and relative wavelet energy of delta, theta, alpha, beta bands of all channels were extracted by the following equations:

$$E_{cD_i} = \sum_{j=1}^{N} \left|cD_{ij}\right|^2, i \in \{1,2,3,\ldots,L\} \tag{5}$$

$$E_{cA_i} = \sum_{j=1}^{N} \left|cA_{ij}\right|^2, i = L \tag{6}$$

$$E_{total} = \left(\sum_{i=1}^{L} E_{cD_i} + E_{cA_i}\right) \tag{7}$$

$$E_r = \frac{E_s}{E_{total}}, E_s = E_{cD_i} or E_{cA_i} \tag{8}$$

where L is the total number of decomposition levels, E_{total} and E_r represent total wavelet energy of all bands, and relative energy of sub-band respectively. Based on Eq. (8), we calculate the relative power of theta and beta bands. Then the indicator of attention can be calculated by extracting relevant channels as Eq. (9) shows:

$$I_a = \frac{E_{theta}(AF3 + AF4 + F3 + F4)}{E_{beta}(AF3 + AF4 + F3 + F4)} \tag{9}$$

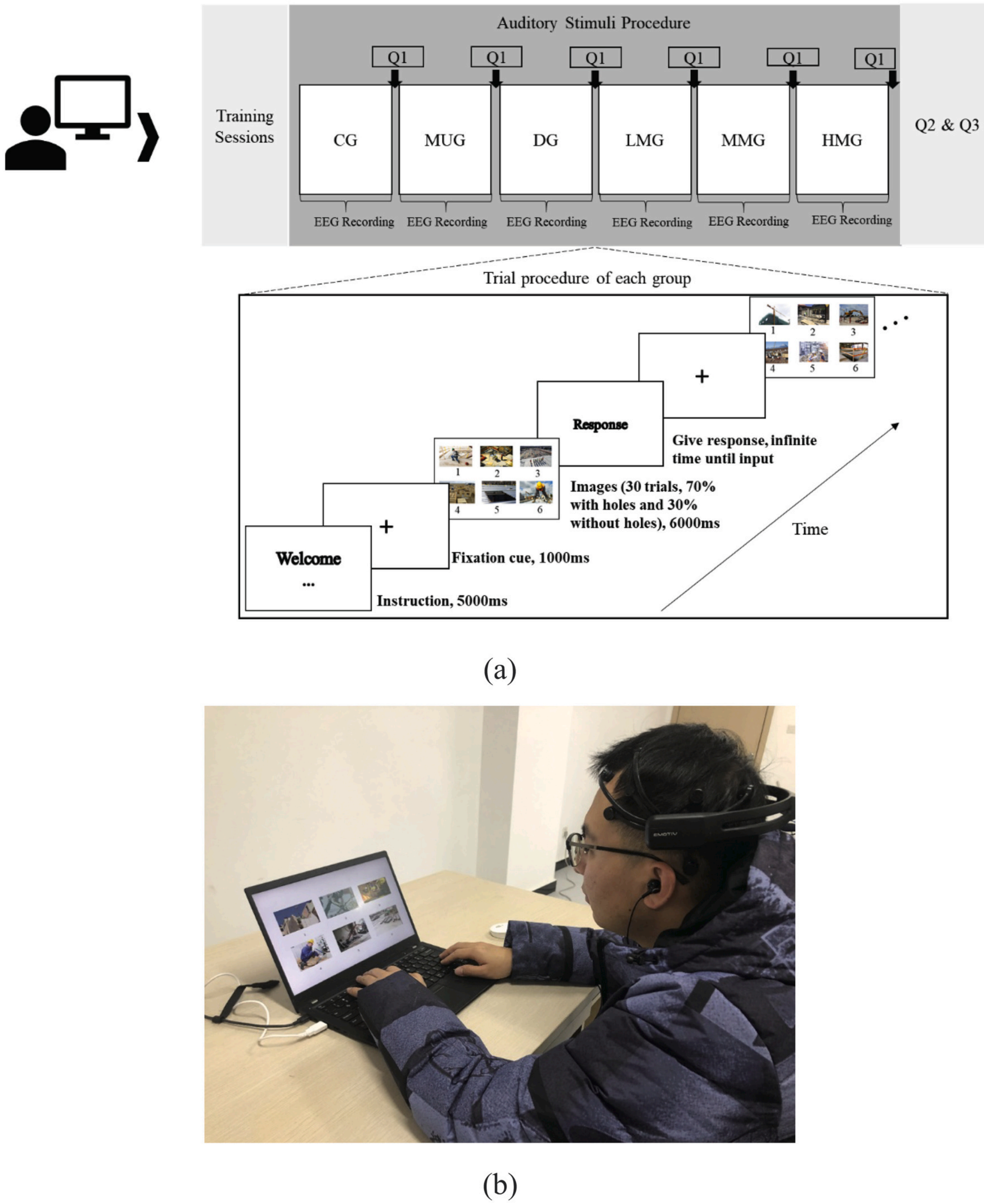

Fig. 4. Experiment scene and procedure. (a) experiment procedure of each subject; (b) a subject wearing EEG headset.

Table 3
Questions presented in each group and the end of the experiment, respectively.

Question	Alternatives
Q1: How would you rate your attentional level?	Five-point Likert scale with 1 indicating "not focused at all" and 5 indicating "extremely focused"
Q2: How do you rank the perceived effect of three types of noise content?	1) Music, 2) Dialogue, 3) Machine (1: not influenced-3: extremely influenced)
Q3: How do you rank the perceived effect of three noise levels?	1) low level, 2) Medium level, 3) High level (1: not influenced-3: extremely influenced)

Similarly, the relative wavelet energy of the alpha band was obtained by Eq. (8). Asymmetry index (ASI) of frontal alpha EEG has determinant effects of stress response implicated by many studies [57]. ASI refers to the left hemisphere's alpha power natural logarithm subtracting that of the right hemisphere, as illustrated by Eq. (10). According to ASI's widely used channels, herein channel adopted is F7–F8, which was estimated as a direct region affected by stress [54].

$$I_s = ln\left(E_{alpha}\right)\big|_{L_{channel-F7}} - ln\left(E_{alpha}\right)\big|_{R_{channel-F8}} \tag{10}$$

For an indicator of mental workload, WENG represents the energy of the approximate coefficients by wavelet analysis, which also reflects energy distribution over the delta band [55]. Herein, WENG is the sum of squares of approximate coefficients of a particular level as given by

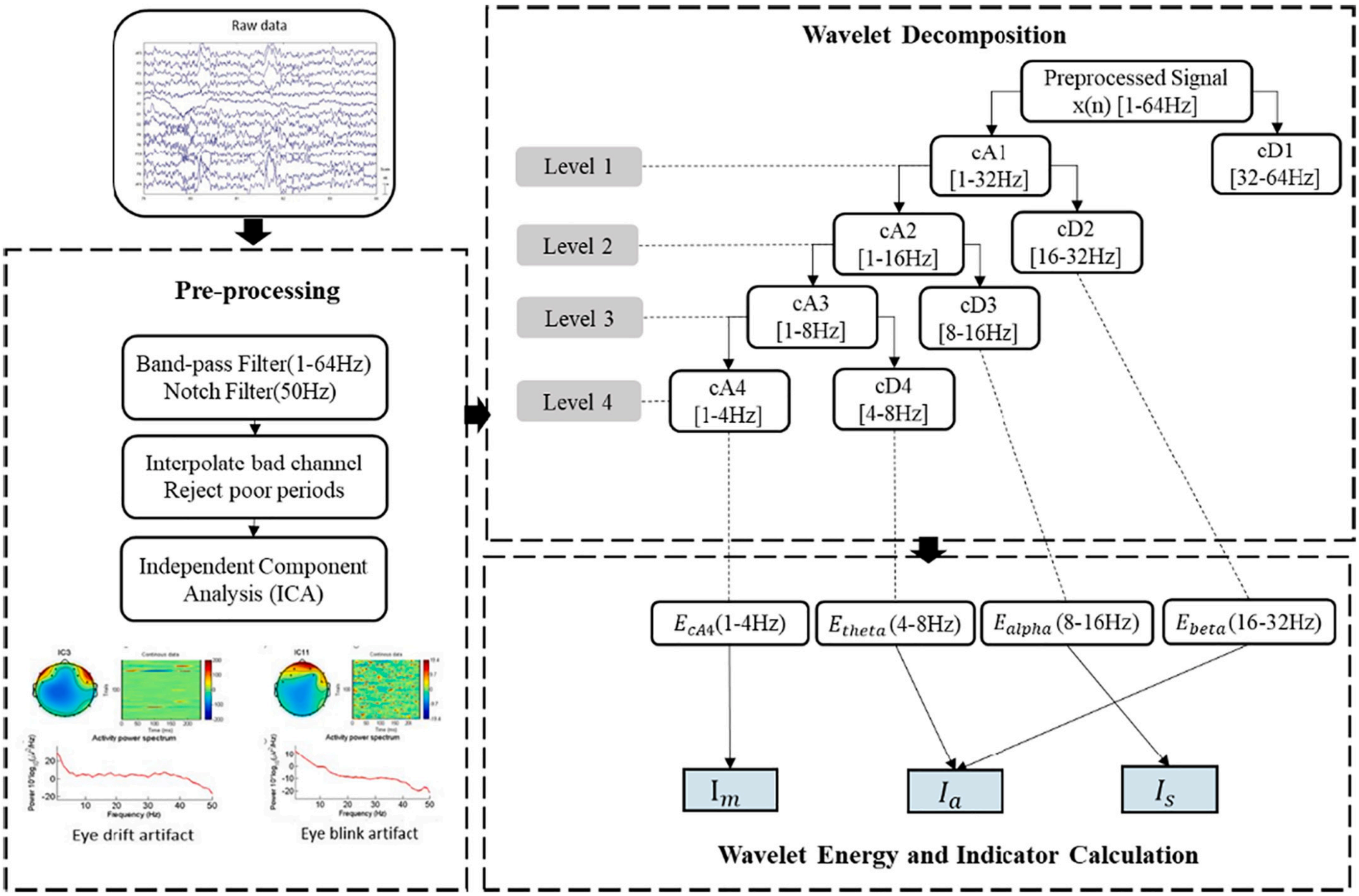

Fig. 5. EEG data processing framework by wavelet decomposition.

the eq. (6) and then extracting related channels:

$$I_m = E_{cA_i}(AF3 + AF4 + F3 + F4 + F7 + F8 + FC5 + FC6) \tag{11}$$

Then normalization was used in each indicator for better comparison on the same scale. Similarly, the Kruskal-Wallis ANOVA test was used to examine the effect of noise content and level on attentional, stress, and mental workload related indicators.

4.3. *Relationship analysis between behavioral and cognitive performance*

The average reaction time and response accuracy of each group were analyzed, and the attentional, stress, mental workload indicators were averaged out for each trial. Preliminarily, scatter diagrams were used as the preliminary analysis on the distribution and the correlation between these two types of data. The Pearson correlation coefficients were also calculated to identify the linear dependence between behavior and cognitive performance metrics. If linear dependence were identified, linear regression analysis would be used to quantify the correlation.

5. Results

The results elaborated in this section were divided into behavior performance, cognitive performance, and interrelation results. Based on behavioral metrics and EEG indicators analysis, the relationship between these two was discussed.

5.1. *The effect of noise on behavioral performance*

Table 4 presents the descriptive statistics of behavior performance metrics: reaction time (RT), response accuracy (RA), rating score of

Table 4
Descriptive results of performance data exposure to distinct noise groups.

	CG		MUG		DG		LMG		MMG		HMG	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Sample Size	$N = 26$*		$N = 27$		N = 27		N = 27		N = 27		N = 27	
Trials	780		810		810		810		810		810	
Accuracy	0.74	0.44	0.80	0.40	0.75	0.43	0.75	0.43	0.69	0.46	0.73	0.45
Q1 score	4.26	0.86	3.93	1.04	3.74	1.02	4.19	0.74	3.89	1.01	3.74	1.26
RT (ms)	831.14	677.45	741.23	702.67	687.86	472.86	651.73	503.41	818.39	621.15	613.92	560.21
Right trials	576		648		607		611		563		588	
RT (correct answers)	728.58	525.76	695.04	700.83	645.66	416.15	598.30	465.21	698.19	410.73	552.33	511.96
Wrong trials	204		162		203		199		247		222	
RT (incorrect answers)	1120.70	929.56	925.98	681.35	814.06	595.46	815.77	576.93	1091.27	880.68	777.06	644.86

* Means sample size of the CG is 26 because of the failure of one subject in the recording software.

questions within the six groups. The results showed that the hazard identification of MUG was the most accurate (0.80), followed by DG and LMG (0.75), CG (0.74), HMG (0.73), lastly, MMG (0.69).

Kruskal-Wallis ANOVA results, as shown in Table 5 regarding the accuracy, showed that the effect of noise content was statistically significant across response accuracy (Chi square = 23.82, df = 3, $p < 0.01$). In contrast, the effect of noise level was not statistically significant across response accuracy (Chi square = 7.72, df = 3, $p = 0.05$). Post-hoc comparisons indicated that the mean for the MUG condition (M = 0.8, SD = 0.14) was significantly different from the MMG condition (mean rank diff = 168.43, z = 3.66, $p < 0.01$).

With respect to the reaction time of all trials, ANOVA results revealed that differences pertaining to both noise content (Chi square = 37.04, df = 3, $p < 0.01$) and noise level (Chi square = 158.0, df = 3, $p < 0.01$). The Post-hoc results suggested the means of response time in the CG was higher than that of MUG (mean rank diff = 174.41, z = 3.75, $p < 0.01$) and DG (mean rank diff = 222.74, z = 4.79). Moreover, the average reaction time had a significant difference between DG and MMG (mean rank diff = −169.56, z = −3.68, $p < 0.01$); MUG and MMG (mean rank diff = −217.89, z = −4.73, $p < 0.01$). Concerning the effect of noise level on reaction time, MMG exhibited significant differences with LMG (mean rank diff = 345.81, z = 7.51, $p < 0.01$) and HMG (mean rank diff = 454.61, z = 9.87, $p < 0.01$).

The analysis above was averaged for all trials of each group regardless of the correctness of each trial. Hence, by separating the trials into wrong and right trials, as shown in Table 4, the Mann-Whitney *U* test of two samples (wrong and right trials) was examined. As shown in Table 6, the right trials exhibited a significantly shorter reaction time for each group ($p < 0.01$) compared with the incorrect answers, which implies that the subjects tend to give incorrect answers when taking more time.

There was no significant difference between the content (Chi-square = 4.19, df = 3, $p = 0.24$) and level (Chi square = 3.47, df = 3, $p = 0.33$) concerning subjective attentional rating scores at a 0.05 significant level. Participants have rated the subjectively perceived effect of noise content and level, and the result was plotted in Fig. 6. Participants' perceptions of the effect of noise content (Chi-square = 9.31, df = 2, $p < 0.01$) and level (Chi-square = 58.14, df = 2, $p < 0.01$) showed significant difference. The post-hoc analysis of rating Q2 suggested that the scores were significant between MUG and DG (mean rank diff = −17.61, z = −2.86, $p = 0.01$) at the 0.05 level. Also, significant difference of Q3 scores were observed in pairwise comparisons between LMG and MMG (mean rank diff = −26.15, z = −4.25, $p < 0.01$), MMG and HMG (mean rank diff = −19.70, z = −3.20, $p < 0.01$), LMG and HMG (mean rank diff = −45.85, z = −7.45, $p < 0.01$).

Table 5
Kruskal-Wallis ANOVA results for behavior metrics.

Metric	IV	df	Chi-Square	Prob>Chi-Square	Post-hoc comparison	p
RA	Content	3	23.82	2.73e-5*	MUG>MMG	< 0.01*
	Level	3	7.72	0.05	NaN	NaN
RT	Content	3	37.04	4.52e-8*	CG > MUG	< 0.01*
					CG > DG	< 0.01*
					MMG > MUG	< 0.01*
					MMG > DG	< 0.01*
	Level	3	158.0	4.96e-34*	CG > LMG	< 0.01*
					CG > HMG	< 0.01*
					MMG > LMG	< 0.01*
					MMG > HMG	< 0.01*

[*] Is the significant value at a 0.05 level.

Table 6
Mann-Whitney U test results of reaction time between wrong and right trials.

Group	U	z	p
CG	38,082	−7.49	6.76e-14*
MUG	35,256	−6.47	9.84e-11*
DG	50,547	−3.83	1.26e-4*
LMG	44,916.5	−5.46	4.81e-8*
MMG	44,383.5	−8.20	2.35e-16*
HMG	43,747	−7.25	4.31e-13*

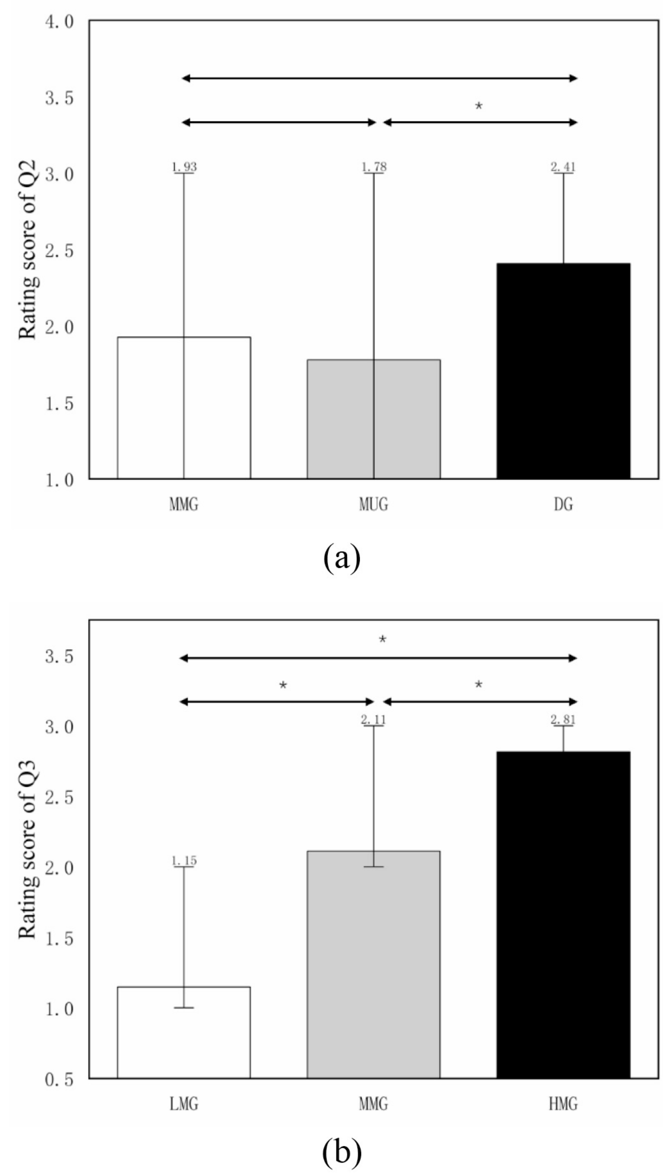

Fig. 6. Mean rating score and comparison for (a) Q2 rating score; (b) Q3 rating score. * represents significant difference by pairwise comparison.

5.2. The effect of noise on EEG signals

Noise content and level exhibited differences in the EEG indicators (I_a,I_s,I_m) among the six groups, as depicted in Fig. 7.

Specific post-test results of attentional, stress-related, and mental workload indicators were summarized in Table 7. As shown in Table 7,

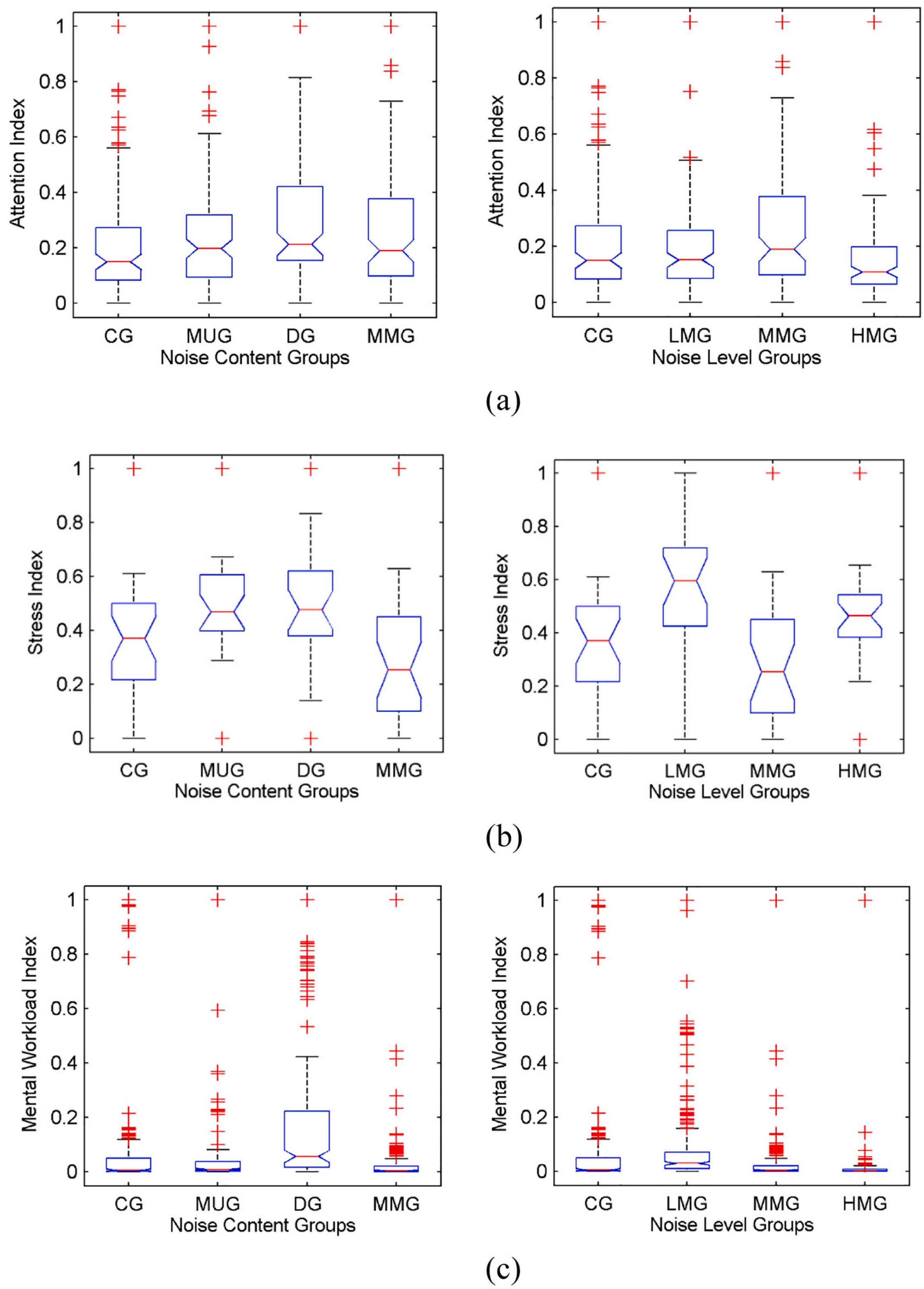

Fig. 7. EEG indicators (a) I_a, (b) I_s, and (c)I_m among six groups.

the effect of noise content (Chi square = 17.28, df = 3, $p < 0.01$) and level (Chi square = 20.23, df = 3, $p < 0.01$) on attention are both significant in terms of I_a. Specifically, the normalized energy of DG was higher than that of CG (mean rank diff = 68.81, z = 4.05, $p < 0.01$) and MUG (mean rank diff = 47.23, z = 2.78, p = 0.03). Moreover, the relative power of the MMG exhibited significant differences from HMG (mean rank diff = 76.16, z = 4.48, $p < 0.01$).

From the I_s comparison, both the effects of noise content (Chi square = 18.58, df = 3, $p < 0.01$) and level (Chi square = 21.62, df = 3, $p < 0.01$) on stress were pronounced. Specifically, the energies of DG (mean rank diff = 29.56, z = 3.47, $p < 0.01$) and MUG (mean rank diff = 31.41, z = 3.68, $p < 0.01$) were significantly higher than that of the MMG. The normalized power in MMG was the lowest among all noise level groups, which was lower than that of LMG (mean rank diff = −37.74, z = −4.43, $p < 0.01$), HMG (mean rank diff = −23.93, z = −2.81, p = 0.03). Moreover, the estimated value in LMG is significantly higher than the power in CG (mean rank diff = 25.85, z = 3.03, p = 0.01).

Regarding the effect of noise content on mental workload measured

Table 7
Kruskal-Wallis ANOVA results for EEG indicators.

Indicator	IV	df	Chi-Square	Prob. > Chi-Square	Post-hoc	p
I_a	Content	3	17.28	6.18e-4*	DG > CG	< 0.01*
					DG > MUG	0.03
	Level	3	20.23	1.52e-4*	MMG > HMG	< 0.01*
I_s	Content	3	18.58	3.34e-4*	DG > MMG	< 0.01*
					MUG>MMG	< 0.01*
	Level	3	21.62	7.81e-5*	LMG > CG	0.01
					LMG > MMG	< 0.01*
					HMG > MMG	0.03
I_m	Content	3	154.93	2.28e-33*	DG > CG	< 0.01*
					DG > MUG	< 0.01*
					DG > MMG	< 0.01*
					MUG>MMG	0.03
	Level	3	156.69	9.50e-34*	LMG > CG	< 0.01*
					LMG > MMG	< 0.01*
					CG > HMG	< 0.01*
					LMG > HMG	< 0.01*
					MMG > HMG	< 0.01*

* Means the significant level far less than 0.01.

by I_m, the power of DG was significantly distinguished from CG (mean rank diff = 227.26, z = 9.46, $p < 0.01$), MUG (mean rank diff = 207.59, z = 8.64, $p < 0.01$), and MMG (mean rank diff = 276.41, z = 11.51, $p < 0.01$). Additionally, the power in MUG was higher than MMG's power (mean rank diff = 68.82, z = 2.87, $p = 0.02$). In terms of the effect of noise level, the power gradually decreased with the increase in volume; that is, the mental workload of the HMG was higher than that of the LMG (mean rank diff = −291.95, z = −12.16, $p < 0.01$) and MMG (mean rank diff = −84.43, z = −3.52, $p < 0.01$).

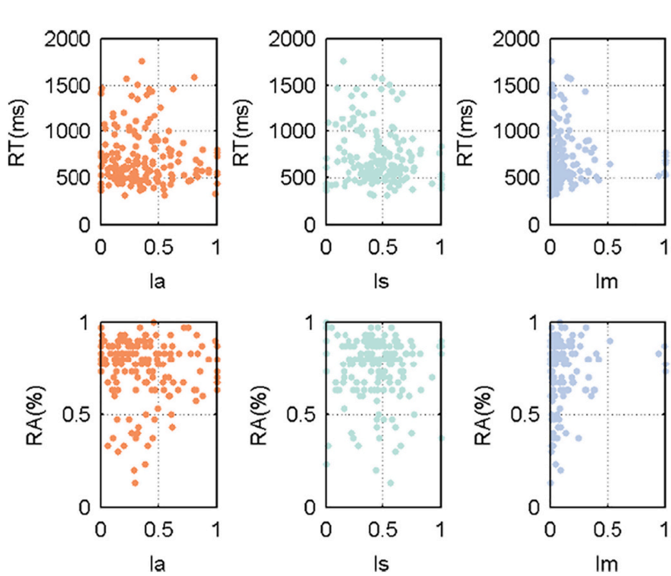

Fig. 8. The scatter distribution between reaction data and EEG indicators.

5.3. The relationship between behavioral and cognitive performance

The scatter diagrams (Fig. 8) showed the distribution between response data and cognitive indicators. No strong linear correlation was observed between behavior metrics and cognitive indicators.

The correlation coefficients were calculated and summarized in Fig. 9. Regarding the linear correlation between these metrics, only RA and RT showed a weak negative correlation ($r = -0.34$), I_m and I_a indicators exhibited a weak positive correlation ($r = 0.25$).

6. Discussion

The section explained the effect concerning noise content and the impact of the noise level and investigated the possible reasons. Then, the limitations and contributions of the study were discussed.

6.1. Implications of results

Noise contents have a remarkable effect on response accuracy, suggesting that music promoted accuracy, whereas the medium level of mechanical noise impaired the accuracy. The cognitive performance by EEG indicators revealed that while music affected concentration, it also reduced stress. The result supports previous studies' findings [38] that background music can partly serve as pleasure stimuli to invoke arousal according to the "arousal and mood hypothesis" [65], thus increasing task engagement and processing speed. Nevertheless, music can be pleasant for student groups, not necessarily for workers, because attention essential for hazards identification has been diverted to music. The effect of noise at a medium level is more harmful to accuracy, and this result can be explained that short memory would be affected significantly by the medium level of noise exposure [13].

Regarding the impact of noise on reaction time, music and conversational dialogue shorten the judgment duration, while the medium level of noise caused by the machine prolonged the duration. The finding is inconsistent with the previous studies that investigate the effect of conversation on reaction behavior [66]. A prior study indicated that conversation leads to an increase in reaction time and errors [67]. Differences in results may stem from the format of the conversation. Those studies demanded subjects to participate in a conversation, but participants in this study merely listened to the conversation from a third-person perspective. According to the subjective feedback, participants agreed that music and dialogue have a more substantial negative effect

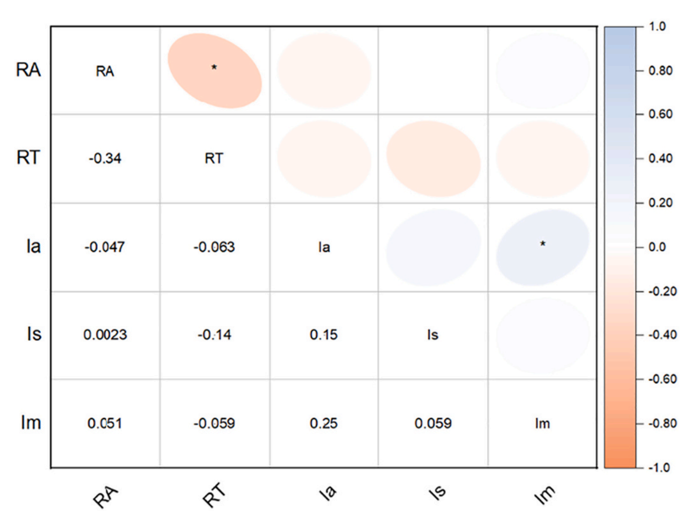

Fig. 9. Correlation coefficients between behavior and cognitive performance metrics. Eclipse represents the corresponding visualization value of region in the lower triangle, the narrower eclipse represents more linear correlation. * represents the significant value lower than 0.05.

than mechanical noise, reporting that they were more attracted by music and dialogue. The subjective feedback is indeed in line with the result of I_a. However, decreased attention does not significantly impact behavior, showing that task difficulty and the conversation engagement degrees are critical factors for behavior performance. It is noted that conversation leads to a higher degree of distracting attention than music. According to Liu's study, which revealed that music without lyrics had less impact and participants performed better than lyrics with music [10]. In this case, conversations have more meaningful content than music, thus resulting in the occupation of more attention resources. It can be observed from I_s that EEG showed the lowest level of perceived stress when the dialogue intervened tasks, which is identical to the lowest mental workload according to I_m. Mental workload is interpreted as the perceived workload for primary work demands and linked with stress positively [68]. Hence, the subjects felt fewer task requirements because of attention drift, leading to less mental workload. It needs to be noted that even though music and dialogue can reduce stress and a certain amount of mental workload, they particularly affect attention.

Mechanical noise significantly increased the mental workload by EEG estimation, compared to music and dialogue. Actually, the research into the effect of noise on mental workload remains inadequate in the area of the construction field compared to other fields like open-plan offices or factories [29,69]. The related study is essential for occupational health and safety improvement. Moreover, mental workload intensified with the increase of noise level, and the trend is similar to the result of Q3. However, the trends of stress and mental workload are not similar. Light mechanical noise reduced stress and the stress reached a maximum in the presence of medium level, which is higher than that of the high noise level. The result disagrees with the findings in other fields that indicated stress is positively correlated with noise levels [70]. The results of this paper show the effect of noise level on stress may exist an inflection point, but its existence needs further experimental exploration to validate. In addition to stress, the medium level of mechanical noise has a severe influence on reaction time and attention. The outcome also contradicts existing studies [30,71]; that is, the higher the level corresponds to the more significant negative impact on attention. One of the explicable views argues that too high or low noise exposure seems to destroy brain steadiness [46]. In contrast, the current research highlights the hazard and importance of the medium level of noise. It is necessary to consider the importance of the medium level of noise, as most employees are practically exposed to noise at a medium level in the construction sector.

6.2. Limitations and prospects

The work is an initial attempt to study the effect of noise on cognitive performance through physiological measurement. The findings are beneficial to explore the internal causes of unsafe behavior and occupational health. Although certain noise types and volume levels are difficult to regulate, their adverse effect can be controlled and modulated according to the findings of the study. For instance, the authors found that the medium level of mechanical noise has a worse influence on stress and attention. For safety-related work personnel, it is important to pay attention to the safety situation when encountering a medium level of mechanical noise by safety warning. Furthermore, this paper provided the basis for further studies because monitoring an individual's cognitive performance is promising and realizable. While the association between cognitive performance and behavior is not as expected, it is still worth exploring the internal causes of unsafe performance via physiological measures. External cause is not easy to control, then we can control internal cause to reduce the probability of unsafe behavior directly.

Several research limitations still need to be addressed in the future research agenda. First, the experiment was conducted in a laboratory other than the realistic workplace. This is because the real construction site is relatively noisy and it is difficult to control the irrelevant variables. Moreover, if the conversation is generated by people talking, it will be difficult for them to maintain the same volume level during the whole process. As for the presentation of noise, using earphones aimed to minimize environmental noise impacts like noise from experimenter operation. Using headphones or earphones is reliable, which has been confirmed by many auditory stimulus studies [72–75]. However, future research is expected to conduct more realistically at the construction workplace. Another difference exists in the participants because adaptation to noise and the knowledge of construction safety between students and workers are discrepant. Additionally, the experiment stimulus location number is fixed, which possibly decreased the task difficulty due to the familiarity with the location sequence. A study has suggested that the influence of noise level and content is also associated with task difficulty. Simple tasks are affected by the noise level, while complex tasks are affected by noise type [13]. In this study, the identifications of unsafe holes are relatively simple tasks because of image 2D presentation and conspicuous holes. However, there are many complex construction activities on the actual site. The effect heavily relies on task difficulty due to noise will compete for inadequate cognitive resources when the worker if facing more complicated tasks. However, cognitive resources seem to remain sufficient when performing simple tasks. Therefore, different characteristics of noise under different task environments may cause far-reaching effects and serious consequences. Another limitation is that noise exposure duration is relatively short compared to worksites, leading to a minor effect than that in practice. Furthermore, the noise type presented is continuous other than intermittent, which is not consistent precisely with the nature of irregular noise like music and dialogue. Though the interrelation of behavioral and cognitive performance has not lived up to expectations, EEG is still a valuable and promising tool for quantifying the cognitive state and establishing a relationship with behavior. In this paper, assessing cognitive performance only by EEG is less rigorous. In future studies, it was supposed to combine cognitive scale tests and physiological measurement to evaluate cognitive performance. In addition to these advocated indicators, other categories of cognitive performance like fatigue, arousal, and annoyance level are expected to investigate the change under different noise conditions at the construction site.

7. Conclusion

Through an experiment to identify hazards, the adverse effects of noise content and level on both behavior and cognitive performance were investigated. Moreover, it was found that reaction time differs across different noise contents and levels; mainly the effect is remarkable of medium level of mechanical noise. The noise content also impacted the cognitive performance, mainly referring to dialogue and music. While conversation and music are the least stressful and conversation particularly lowers the mental workload, attention decreased significantly in confront with dialogue and music. Contrary to expectations regarding the noise level, medium noise levels exhibited a stronger negative effect on attentional and stress change than high level. This highlights the importance of a medium noise level, which may correlate well with the inflection point of attention and stress. Moreover, the mechanical noise increased mental workload significantly with the increase in level. The different trend indicates stress and mental workload are not always positively correlated. The findings give insights into noise contents and levels' effects on cognitive status, to ensure better noise and safety management. The carried experiment merely considered continuous noise, and a type of task and future research should involve more realistic experiments and safety-critical scenarios.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] S.C. Lee, J.H. Kim, J.Y. Hong, Characterizing perceived aspects of adverse impact of noise on construction managers on construction sites, Build. Environ. 152 (2019) 17–27, https://doi.org/10.1016/j.buildenv.2019.02.005.
[2] M.D. Fernández, S. Quintana, N. Chavarría, J.A. Ballesteros, Noise exposure of workers of the construction sector, Appl. Acoust. 70 (2009) 753–760, https://doi.org/10.1016/j.apacoust.2008.07.014.
[3] A. Daiber, S. Kröller-Schön, K. Frenis, M. Oelze, S. Kalinovic, K. Vujacic-Mirski, M. Kuntic, M.T. Bayo Jimenez, J. Helmstädter, S. Steven, B. Korac, T. Münzel, Environmental noise induces the release of stress hormones and inflammatory signaling molecules leading to oxidative stress and vascular dysfunction—signatures of the internal exposome, BioFactors. 45 (2019) 495–506, https://doi.org/10.1002/biof.1506.
[4] M. Picard, S. André, M. Simard, R. Larocque, T. Leroux, F. Turcotte, Association of work-related accidents with noise exposure in the workplace and noise-induced hearing loss based on the experience of some 240000 person-years of observation, Accident Anal. Prevent. J. 40 (2008) 1644–1652, https://doi.org/10.1016/j.aap.2008.05.013.
[5] A.H. Suter, Construction noise: exposure, effects, and the potential for remediation; a review and analysis, Am. Ind. Hyg. Assoc. J. 63 (2002) 768–789, https://doi.org/10.1080/15428110208984768.
[6] A. Smith, Noise, performance efficiency and safety, Int. Arch. Occup. Environ. Health 61 (1990) 1–5, https://doi.org/10.1007/BF00397841.
[7] F.J.. van Dijk, Epidemiological research on non-auditory effect of occupational noise exposure, Environ. Int. 16 (1990) 405–409. doi:https://doi.org/10.1016/0160-4120(90)90009-U.
[8] J.L. Szalma, P.A. Hancock, Noise effects on human performance: a meta-analytic synthesis, Psychol. Bull. 137 (2011) 682–707, https://doi.org/10.1037/a0023987.
[9] K. Lewkowski, I.W. Li, L. Fritschi, W. Williams, J.S. Heyworth, A systematic review of full-shift, noise exposure levels among construction workers: are we improving? Annals Work Expos. Health. 62 (2018) 771–782, https://doi.org/10.1093/annweh/wxy051.
[10] T. Liu, C.C. Lin, K.C. Huang, Y.C. Chen, Effects of noise type, noise intensity, and illumination intensity on reading performance, Appl. Acoust. 120 (2017) 70–74, https://doi.org/10.1016/j.apacoust.2017.01.019.
[11] P. Nassiri, M.R. Monazzam, M. Asghari, S.A. Zakerian, S.F. Dehghan, B. Folladi, K. Azam, The interactive effect of industrial noise type, level and frequency characteristics on occupational skills, Perform. Enhanc. Health 3 (2014) 61–65, https://doi.org/10.1016/j.peh.2015.01.001.
[12] P.M. Arezes, S. Barbosa, A.S. Miguel, Noise as a cognitive impairment factor: a case study amongst teachers, in: Proceedings of 20th International Congress on Acoustics, Sydney, 2010, pp. 1–5, in: https://www.acoustics.asn.au/conference_proceedings/ICA2010/cdrom-ICA2010/papers/p114.pdf.
[13] R. Golmohammadi, E. Darvishi, J. Faradmal, J. Poorolajal, M. Aliabadi, Attention and short-term memory during occupational noise exposure considering task difficulty, Appl. Acoust. 158 (2020) 107065, https://doi.org/10.1016/j.apacoust.2019.107065.
[14] J. Reynolds, A. McClelland, A. Furnham, An investigation of cognitive test performance across conditions of silence, background noise and music as a function of neuroticism, Anxiety Stress Coping 27 (2014) 410–421, https://doi.org/10.1080/10615806.2013.864388.
[15] K.N. Kannass, J. Colombo, The effects of continuous and intermittent distractors on cognitive performance and attention in preschoolers, J. Cogn. Dev. 8 (2007) 63–77, https://doi.org/10.1207/s15327647jcd0801_3.
[16] M. Basner, M. Brink, A. Bristow, Y. De Kluizenaar, L. Finegold, J. Hong, S. A. Janssen, R. Klaeboe, T. Leroux, A. Liebl, T. Matsui, D. Schwela, M. Sliwinska-Kowalska, P. Sörqvist, ICBEN review of research on the biological effects of noise 2011–2014, Noise Health 17 (2015) 57–82, https://doi.org/10.4103/1463-1741.153373.
[17] X. Li, Z. Song, T. Wang, Y. Zheng, X. Ning, Health impacts of construction noise on workers: a quantitative assessment model based on exposure measurement, J. Clean. Prod. 135 (2016) 721–731, https://doi.org/10.1016/j.jclepro.2016.06.100.
[18] P.M. Arezes, A.S. Miguel, Hearing protection use in industry: the role of risk perception, Saf. Sci. 43 (2005) 253–267, https://doi.org/10.1016/j.ssci.2005.07.002.
[19] O. Hahad, J.H. Prochaska, A. Daiber, T. Muenzel, Environmental noise-induced effects on stress hormones, oxidative stress, and vascular dysfunction: key factors in the relationship between Cerebrocardiovascular and psychological disorders, Oxidative Med. Cell. Longev. 2019 (2019) 1–13, https://doi.org/10.1155/2019/4623109.
[20] A.M. Abbasi, M. Motamedzade, M. Aliabadi, R. Golmohammadi, L. Tapak, Study of the physiological and mental health effects caused by exposure to low-frequency noise in a simulated control room, Build. Acoust. 25 (2018) 233–248, https://doi.org/10.1177/1351010X18779518.
[21] A.P. Smith, Noise and occupational health and safety, in: Proceedings of First European Forum on Efficient Solutions for Managing Occupational Noise Risks, 2007, pp. 851–856 (Noise at Work 2007. Lille, France), https://www.researchgate.net/profile/Andrew-Smith-36/publication/279848120_Noise_and_Occupational_Health_and_Safety/links/559bb49308ae0035df23263e/Noise-and-Occupational-Health-and-Safety.pdf.
[22] P.M. Arezes, A.S. Miguel, Risk perception and safety behaviour: a study in an occupational environment, Saf. Sci. 46 (2008) 900–907, https://doi.org/10.1016/j.ssci.2007.11.008.
[23] W.S. Helton, G. Matthews, J.S. Warm, Stress state mediation between environmental variables and performance: the case of noise and vigilance, Acta Psychol. 130 (2009) 204–213, https://doi.org/10.1016/j.actpsy.2008.12.006.
[24] F.B.R. Parmentier, The cognitive determinants of behavioral distraction by deviant auditory stimuli: a review, Psychol. Res. 78 (2014) 321–338, https://doi.org/10.1007/s00426-013-0534-4.
[25] E.M. Elmenhorst, D. Elmenhorst, J. Wenzel, J. Quehl, U. Mueller, H. Maass, M. Vejvoda, M. Basner, Effects of nocturnal aircraft noise on cognitive performance in the following morning: dose-response relationships in laboratory and field, Int. Arch. Occup. Environ. Health 83 (2010) 743–751, https://doi.org/10.1007/s00420-010-0515-5.
[26] T. Saeki, T. Fujii, S. Yamaguchi, S. Harima, Effects of acoustical noise on annoyance, performance and fatigue during mental memory task, Appl. Acoust. 65 (2004) 913–921, https://doi.org/10.1016/j.apacoust.2003.12.005.
[27] M.A. Staal, Stress, Cognition, and Human Performance: A Literature Review and Conceptual Framework. NASA/TM-2004-212824, Ames Research Center, Moffett Field, 2004. https://ntrs.nasa.gov/citations/20060017835.
[28] P. Tassi, O. Rohmer, A. Bonnefond, F. Margiocchi, F. Poisson, S. Schimchowitsch, Long term exposure to nocturnal railway noise produces chronic signs of cognitive deficits and diurnal sleepiness, J. Environ. Psychol. 33 (2013) 45–52, https://doi.org/10.1016/j.jenvp.2012.10.003.
[29] T.L. Smith-Jackson, K.W. Klein, Open-plan offices: task performance and mental workload, J. Environ. Psychol. 29 (2009) 279–289, https://doi.org/10.1016/j.jenvp.2008.09.002.
[30] M.J. Jafari, R. Khosrowabadi, S. Khodakarim, F. Mohammadian, The effect of noise exposure on cognitive performance and brain activity patterns, Open Access Macedonian J. Med. Sci. 7 (2019) 2924–2931, https://doi.org/10.3889/oamjms.2019.742.
[31] R. Hoskin, M.D. Hunter, P.W.R. Woodruff, Stress improves selective attention towards emotionally neutral left ear stimuli, Acta Psychol. 151 (2014) 214–221, https://doi.org/10.1016/j.actpsy.2014.06.010.
[32] R.M. Yerkes, J.D. Dodson, The relation of strength of stimulus to rapidity of habit-formation, Punishment: Issues Exp. (1908) 27–41. http://psychclassics.yorku.ca/Yerkes/Law/.
[33] M. Abbasi, S. Yazdanirad, P. Habibi, S. Arabi, R. Fallah Madvari, A. Mehri, M. Poursadeghiyan, M.H. Ebrahimi, M. Ghaljahi, Relationship among noise exposure, sensitivity, and noise annoyance with job satisfaction and job stress in a textile industry, Noise Vibration Worldwide 50 (2019) 195–201, https://doi.org/10.1177/0957456519853812.
[34] S.M. Khan, S. Mir, Z.S. Khan, Assessing Noise Sensitivity on Psycho-Physiological Parameters, February 16, 2019, https://doi.org/10.2139/Ssrn.3335660. Available at SSRN.
[35] D. Schreckenberg, S. Benz, C. Belke, U. Möhler, R. Guski, The relationship between aircraft sound levels, noise annoyance and mental well-being: An analysis of moderated mediation, in: Proceedings of the 12th ICBEN Congress on Noise as a Public Health Problem, 2017, pp. 1–13. http://www.icben.org/2017/ICBEN2017Papers/SubjectArea03_Schreckenberg_0326_3635.pdf.
[36] P. Nassiri, M. Monazam, B. Fouladi Dehaghi, L. Ibrahimi Ghavam Abadi, S. Zakerian, K. Azam, The effect of noise on human performance: a clinical trial, Int. J. Occup. Environ. Med. 4 (2013) 87–95. https://www.theijoem.com/ijoem/index.php/ijoem/article/view/212.
[37] R.W. Hughes, M.J. Hurlstone, J.E. Marsh, D.M. Jones, F. Vachon, Cognitive control of auditory distraction: impact of task difficulty, foreknowledge, and working memory capacity supports duplex-mechanism account, J. Exp. Psychol. Hum. Percept. Perform. 39 (2013) 539–553, https://doi.org/10.1037/a0029064.
[38] S. Bottiroli, A. Rosi, R. Russo, T. Vecchi, E. Cavallini, The cognitive effects of listening to background music on older adults: processing speed improves with upbeat music, while memory seems to benefit from both upbeat and downbeat music, Front. Aging Neurosci. 6 (2014) 1–7, https://doi.org/10.3389/fnagi.2014.00284.
[39] M. Klatte, T. Lachmann, S. Schlittmeier, J. Hellbruck, The irrelevant sound effect in short-term memory: is there developmental change? Eur. J. Cogn. Psychol. 22 (2010) 1168–1191, https://doi.org/10.1080/09541440903378250.
[40] A. Marois, J.E. Marsh, F. Vachon, Is auditory distraction by changing-state and deviant sounds underpinned by the same mechanism? Evidence from pupillometry, Biol. Psychol. 141 (2019) 64–74, https://doi.org/10.1016/j.biopsycho.2019.01.002.
[41] M.K. Robison, N. Unsworth, Working memory capacity offers resistance to mind-wandering and external distraction in a context-specific manner, Appl. Cogn. Psychol. 29 (2015) 680–690, https://doi.org/10.1002/acp.3150.
[42] P.E. Wais, A. Gazzaley, The impact of auditory distraction on retrieval of visual memories, Psychon. Bull. Rev. 18 (2011) 1090–1097, https://doi.org/10.3758/s13423-011-0169-7.
[43] B.R.C. Molesworth, D. Seneviratne, C. Wilcock, Communicating safety information: Investigating how distractors affect the recall of key safety information in pre-flight safety briefings, Appl. Ergon. 81 (2019), https://doi.org/10.1016/j.apergo.2019.102899.

[44] D.E. Broadbent, The current state of noise research: reply to Poulton, Psychol. Bull. 85 (1978) 1052–1067, https://doi.org/10.1037/0033-2909.85.5.1052.
[45] B.B. Van Acker, D.D. Parmentier, P. Vlerick, J. Saldien, Understanding mental workload: from a clarifying concept analysis toward an implementable framework, Cogn. Tech. Work 20 (2018) 351–365, https://doi.org/10.1007/s10111-018-0481-3.
[46] F. Dehais, A. Lafont, R. Roy, S. Fairclough, A Neuroergonomics approach to mental workload, engagement and human performance, Front. Neurosci. 14 (2020) 1–17, https://doi.org/10.3389/fnins.2020.00268.
[47] A.B. Becker, J.S. Warm, W.N. Dember, P.A. Hancock, Effects of jet engine noise and performance feedback on perceived workload in a monitoring task, Int. J. Aviat. Psychol. 5 (1995) 49–62, https://doi.org/10.1207/s15327108ijap0501_4.
[48] P. Leather, D. Beale, L. Sullivan, Noise, psychosocial stress and their interaction in the workplace, J. Environ. Psychol. 23 (2003) 213–222, https://doi.org/10.1016/S0272-4944(02)00082-8.
[49] A. Mehri, I. Alimohammadi, H. Ebrahimi, R. Hajizadeh, M. Roudbari, Effect of traffic noise on mental performance with regard to introversion and task complexity, Appl. Acoust. 132 (2018) 118–123, https://doi.org/10.1016/j.apacoust.2017.11.019.
[50] A. Mursali, E. Basuki, S. Dharmono, Relationship between noise and job stress at a private thread spinning company, Universa Medicina 28 (2016) 8–16, https://doi.org/10.18051/UnivMed.2009.v28.8-16.
[51] D.S. Michaud, K. Feder, S.E. Keith, S.A. Voicescu, L. Marro, J. Than, M. Guay, A. Denning, T. Bower, P.J. Villeneuve, E. Russell, G. Koren, F. van den Berg, Self-reported and measured stress related responses associated with exposure to wind turbine noise, J. Acoust. Soc. Am. 139 (2016) 1467–1479, https://doi.org/10.1121/1.4942402.
[52] G.W. Evans, D. Johnson, Stress and open-office noise, J. Appl. Psychol. 85 (2000) 779–783, https://doi.org/10.1037/0021-9010.85.5.779.
[53] P. Putman, B. Verkuil, E. Arias-Garcia, I. Pantazi, C. Van Schie, EEG theta/beta ratio as a potential biomarker for attentional control and resilience against deleterious effects of stress on attention, Cogn. Affect. Behav. Neurosci. 14 (2014) 782–791, https://doi.org/10.3758/s13415-013-0238-7.
[54] G. Giannakakis, D. Grigoriadis, K. Giannakaki, O. Simantiraki, A. Roniotis, M. Tsiknakis, Review on psychological stress detection using biosignals, IEEE Trans. Affect. Comput. (2019) 1–22, https://doi.org/10.1109/TAFFC.2019.2927337.
[55] P. Zarjam, J. Epps, N.H. Lovell, Beyond subjective self-rating: EEG signal classification of cognitive workload, IEEE Trans. Auton. Ment. Dev. 7 (2015) 301–310, https://doi.org/10.1109/TAMD.2015.2441960.
[56] P. Putman, J. van Peer, I. Maimari, S. van der Werff, EEG theta/beta ratio in relation to fear-modulated response-inhibition, attentional control, and affective traits, Biol. Psychol. 83 (2010) 73–78, https://doi.org/10.1016/j.biopsycho.2009.10.008.
[57] N.L. Lopez-Duran, R. Nusslock, C. George, M. Kovacs, Frontal EEG asymmetry moderates the effects of stressful life events on internalizing symptoms in children at familial risk for depression, Psychophysiology. 49 (2012) 510–521, https://doi.org/10.1111/j.1469-8986.2011.01332.x.
[58] Michiel Spapé, Rinus Verdonschot, Henk van Steenbergen, The E-Primer: An Introduction to Creating Psychological Experiments in E-Prime, Second, Leiden University Press (LUP), Leiden, 2019. http://hdl.handle.net/1887/80357.
[59] M.D. Mrazek, J. Smallwood, J.W. Schooler, Mindfulness and mind-wandering: finding convergence through opposing constructs, Emotion. 12 (2012) 442–448, https://doi.org/10.1037/a0026678.
[60] I. Kawashima, H. Kumano, Prediction of mind-wandering with electroencephalogram and non-linear regression modeling, Front. Hum. Neurosci. 11 (2017) 1–10, https://doi.org/10.3389/fnhum.2017.00365.
[61] G. Kim, W. Han, Sound pressure levels generated at risk volume steps of portable listening devices: types of smartphone and genres of music, BMC Public Health 18 (2018) 1–7, https://doi.org/10.1186/s12889-018-5399-4.
[62] A. Delorme, S. Makeig, EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis, J. Neurosci. Methods 134 (2004) 9–21, https://doi.org/10.1016/j.jneumeth.2003.10.009.
[63] H.U. Amin, A.S. Malik, R.F. Ahmad, N. Badruddin, N. Kamel, M. Hussain, W.-T. Chooi, Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques, Aust. Phys. Eng. Sci. Med. 38 (2015) 139–149, https://doi.org/10.1007/s13246-015-0333-x.
[64] I. Daubechies, B.J. Bates, Ten lectures on wavelets, J. Acoust. Soc. Am. 93 (1993) 1671, https://doi.org/10.1121/1.406784.
[65] W.F. Thompson, E.G. Schellenberg, G. Husain, Arousal, mood, and the Mozart effect, Psychol. Sci. 12 (2001) 248–251, https://doi.org/10.1111/1467-9280.00345.
[66] S. Amado, P. Ulupinar, The effects of conversation on attention and peripheral detection: is talking with a passenger and talking on the cell phone different? Transport. Res. F: Traffic Psychol. Behav. 8 (2005) 383–395, https://doi.org/10.1016/j.trf.2005.05.001.
[67] M.A. Kunar, L. Cole, A. Cox, J. Ocampo, It is not good to talk: conversation has a fixed interference cost on attention regardless of difficulty, Cogn. Res. Princ. Implic. 3 (2018), https://doi.org/10.1186/s41235-018-0124-5.
[68] N.H. Alsuraykh, M.L. Wilson, P. Tennent, S. Sharples, How Stress and Mental Workload are Connected, ACM International Conference Proceeding Series, 2019, pp. 371–376, https://doi.org/10.1145/3329189.3329235.
[69] G.B. Reid, T.E. Nygren, Human Mental Workload, 1988, https://doi.org/10.1007/978-3-030-62302-9.
[70] A. Arabacı, E. Önler, The effect of noise levels in the operating room on the stress levels and workload of the operating room team, J. Perianesthesia Nursing. 36 (2021) 54–58, https://doi.org/10.1016/j.jopan.2020.06.024.
[71] R. Monteiro, D. Tomé, P. Neves, D. Silva, M.A. Rodrigues, The interactive effect of occupational noise on attention and short-term memory: a pilot study, Noise Health 20 (2018) 190–198, https://doi.org/10.4103/nah.NAH_3_18.
[72] K.D. Ponjavic-Conte, J.R. Dowdall, D.A. Hambrook, A. Luczak, M.S. Tata, Neural correlates of auditory distraction revealed in theta-band EEG, NeuroReport. 23 (2012) 240–245, https://doi.org/10.1097/WNR.0b013e3283505ac6.
[73] N. Dahal, D.N. Nandagopal, B. Cocks, TVAR modeling of EEG to detect audio distraction during simulated driving, J. Neural Eng. 11 (2014) 1–14, https://doi.org/10.1088/1741-2560/11/3/036012.
[74] S. Aliakbaryhosseinabadi, E.N. Kamavuako, N. Jiang, D. Farina, N. Mrachacz-Kersting, Classification of EEG signals to identify variations in attention during motor task execution, J. Neurosci. Methods 284 (2017) 27–34, https://doi.org/10.1016/j.jneumeth.2017.04.008.
[75] S. Schall, C. Quigley, S. Onat, P. König, Visual stimulus locking of EEG is modulated by temporal congruency of auditory stimuli, Exp. Brain Res. 198 (2009) 137–151, https://doi.org/10.1007/s00221-009-1867-5.